

## Stat 342 Example 33

Consider  $\underline{z} = (y_1, y_2, \dots, y_n)$  with iid Exponential mean  $\mu$  components  $y_i$ . The log-likelihood is

$$\begin{aligned}\ln f(\underline{z} | \mu) &= \ln \left( \prod_{i=1}^n \frac{1}{\mu} \exp\left(-\frac{y_i}{\mu}\right) \right) \\ &= -n \ln \mu - \frac{1}{\mu} \sum y_i\end{aligned}$$

So the "score function" (of  $\mu$ ) is

$$\frac{\partial}{\partial \mu} \ln f(\underline{z} | \mu) = -\frac{n}{\mu} + \frac{1}{\mu^2} \sum y_i$$

and the "likelihood equation" is

$$\frac{\partial}{\partial \mu} \ln f(\underline{z} | \mu) = 0$$

i.e.

$$-\frac{n}{\mu} + \frac{1}{\mu^2} \sum y_i = 0$$

which has the unique solution for  $\mu$  of  $\mu = \bar{y}$ .  $\bar{y}$  is in fact not only the only root of the likelihood equation, but also the unique maximizer of the likelihood, i.e.

$$\hat{\mu}_n^{MLE} = \bar{y}_n$$

Maximum likelihood theory OR the LLN promises that for any  $\epsilon > 0$

$$P_{\mu_0} \left[ \left| \hat{\mu}_n^{MLE} - \mu_0 \right| > \epsilon \right] \rightarrow 0$$

The distribution of  $\hat{\mu}_n^{MLE}$  piles up at the "true value" of  $\mu$  (the value under which probabilities are being calculated).

The FI in any  $y_i$  about  $\mu$  can be gotten as follows.

$$\ln f(y|\mu) = -\ln \mu - \frac{y}{\mu}$$

$$\frac{\partial}{\partial \mu} \left( \right) = -\frac{1}{\mu} + \frac{y}{\mu^2}$$

$$\text{Var}_{\mu} \left( \right) = \frac{1}{\mu^4} \text{Var}_{\mu}(y) = \frac{1}{\mu^4} (\mu^2) = \frac{1}{\mu^2}$$

So maximum likelihood theory says that

$$(*) \quad \frac{\hat{\mu}_n^{MLE} - \mu}{\sqrt{\frac{1}{n I_y(\mu)}}} = \frac{\bar{y} - \mu}{\sqrt{\frac{1}{n(\frac{1}{\mu^2})}}} = \frac{\bar{y} - \mu}{\frac{\mu}{\sqrt{n}}}$$

is approximately standard normal. Since  $\mu_y = \mu$  and  $\sigma_y = \mu$  This is also

$$\frac{\bar{y} - \mu_y}{\sigma_y / \sqrt{n}}$$

and so this follows also from the CLT.

This means that limits

$$\bar{y} \pm z \frac{\mu}{\sqrt{n}}$$

are valid but unusable large  $n$  approximate confidence limits for  $\mu$ . They can be "fixed" by fixing the use of  $n I_y(\mu)$  in (\*). Fix #1 (the "expected information" fix) is to use instead  $n I_y(\hat{\mu}_n^{MLE})$ . This is  $\frac{n}{\bar{y}^2}$  yielding limits

$$\bar{y} \pm z \frac{\bar{y}}{\sqrt{n}} \quad \text{i.e.} \quad \bar{y} \left( 1 \pm z \frac{1}{\sqrt{n}} \right)$$

Fix 2 (the "observed information" fix) is to replace  $n I_y(\mu)$  with the negative curvature of the log-likelihood at the MLE. Then

$$\begin{aligned} - \frac{\partial^2}{\partial \mu^2} \ln f(\underline{x} | \mu) \Big|_{\mu = \bar{y}} &= \left( -\frac{n}{\mu^2} + \frac{2}{\mu^3} \sum y_i \right) \Big|_{\mu = \bar{y}} \\ &= -\frac{n}{\bar{y}^2} + \frac{2}{\bar{y}^3} \sum y_i \\ &= \frac{n}{\bar{y}^2} \end{aligned}$$

So in this case, the 2nd fix works out to be exactly the same as the first.